Assignment 4

Report

```
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

import numpy as np
import torch
from torch import nn
import torch.nn.functional as F
import pandas as pd
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

```
 %tensorflow_version 2.x
 from __future__ import absolute_import, division, print_function, unicode_literals
import functools
import os
import pandas as pd
import matplotlib.pyplot as plt
from keras.datasets import mnist
from matplotlib import pyplot

import numpy as np
import tensorflow as tf
import pandas as pd
import numpy as np
import torch
import torchvision
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

from torchvision.transforms import transforms
from torch.utils.data import DataLoader
from torch.utils.data import Dataset
```

```
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

import numpy as np
import torch
from torch import nn
import torch.nn.functional as F
import pandas as pd
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
# Reading the data and selecting the rows
data = pd.read_csv('17078.csv')
x =data.iloc[:,0:784].values
y= data.iloc[:,784].values
print(len(y))
```

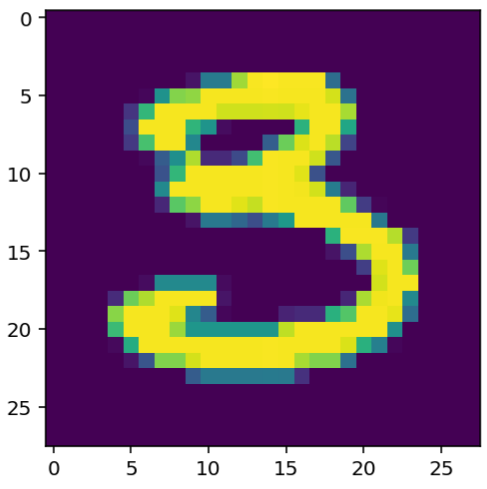
```
#Spliting the data in training and test data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y, test_size = 0.25, random_state = 0,shuffle=True)
```

```
3000
```

Visulalizing the data

```

pixels = x_train[9].reshape(28,28)
plt.imshow(pixels)
print(y_train[9])
```

```
3
```



Preprocessing the data

Scaling these values to a range of 0 to 1 before feeding them to the neural network model. To do so, I divided the values by 255

```

x_train = x_train/255
x_test = x_test/255
```

```
pixels = x_train[1].reshape(28,28)
plt.imshow(pixels)
```

```
<matplotlib.image.AxesImage at 0x7f3bb648d630>
```

Building the model

I am bulding a fully connected neural network with input dimenssion 784 and output dimenssion is 10. In only has one hidden layer

The input and hidden layer has sigmoid activation function because the train data contain both positive and negative values.

The output layer has Softmax activation function.

```
import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from torch import nn
bclfr = Sequential()

bclfr.add(Dense(units = 128 ,kernel_initializer ='uniform',activation = 'sigmoid', input_dim =784))
bclfr.add(Dense(units = 64 , kernel_initializer = 'uniform',activation ='sigmoid'))
bclfr.add(Dense(units = 10 ,kernel_initializer='uniform',activation='softmax'))
```

I am using stochastic gradient descent for optimizing with leaning rate of 0.01 and sparse_categorical_crossentrop as a loss function

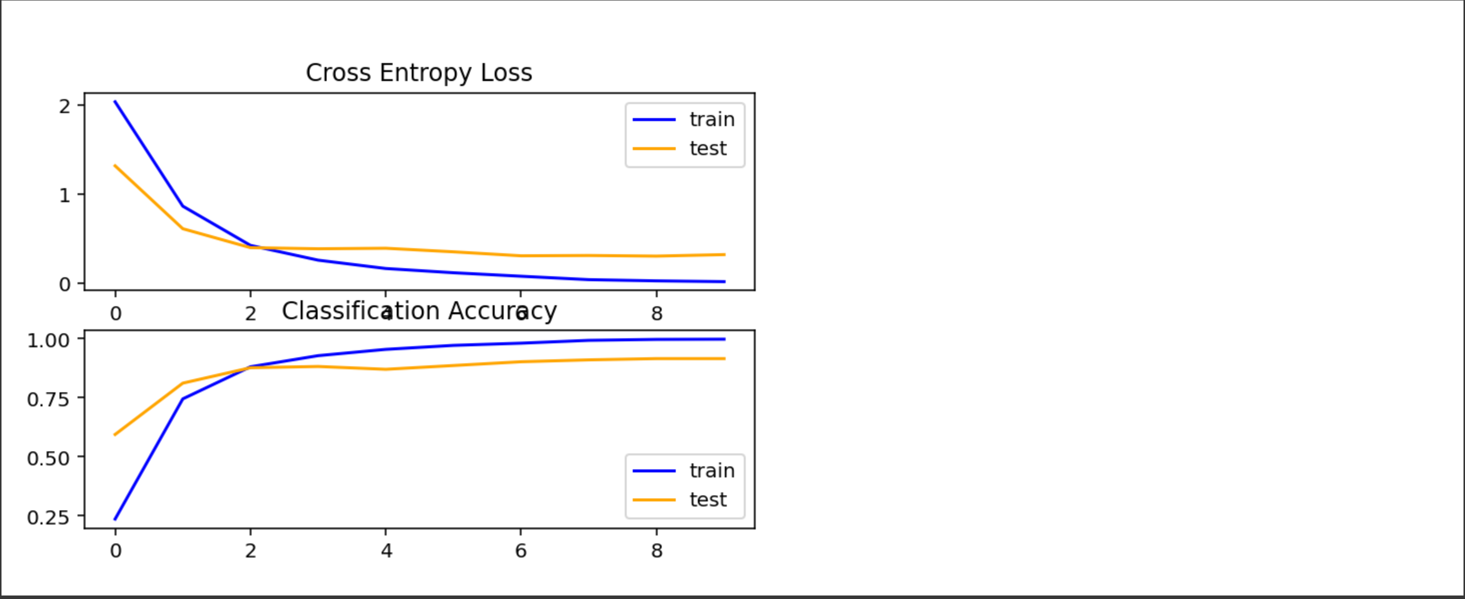
```
bclfr.compile(optimizer=tf.keras.optimizers.Adam(0.01),loss='sparse_categorical_crossentropy',metrics=['accu
history =[]
history.append(bclfr.fit(x_train,y_train,batch_size=64,epochs = 10,validation_data=(x_test,y_test)));
```

```
Epoch 1/10
36/36 [==============================] - 0s 6ms/step - loss: 2.0368 - accuracy: 0.2364 - val_loss: 1.3175 - va
Epoch 2/10
36/36 [==============================] - 0s 4ms/step - loss: 0.8647 - accuracy: 0.7453 - val_loss: 0.6111 - va
Epoch 3/10
36/36 [==============================] - 0s 3ms/step - loss: 0.4240 - accuracy: 0.8813 - val_loss: 0.3982 - v
Epoch 4/10
36/36 [==============================] - 0s 4ms/step - loss: 0.2579 - accuracy: 0.9284 - val_loss: 0.3858 - v
Epoch 5/10
36/36 [==============================] - 0s 4ms/step - loss: 0.1641 - accuracy: 0.9551 - val_loss: 0.3916 - va
Epoch 6/10
36/36 [==============================] - 0s 3ms/step - loss: 0.1165 - accuracy: 0.9720 - val_loss: 0.3515 - va
Epoch 7/10
36/36 [==============================] - 0s 4ms/step - loss: 0.0772 - accuracy: 0.9813 - val_loss: 0.3068 - v
Epoch 8/10
36/36 [==============================] - 0s 4ms/step - loss: 0.0389 - accuracy: 0.9933 - val_loss: 0.3104 - v
Epoch 9/10
36/36 [==============================] - 0s 4ms/step - loss: 0.0253 - accuracy: 0.9973 - val_loss: 0.3033 - v
Epoch 10/10
36/36 [==============================] - 0s 3ms/step - loss: 0.0166 - accuracy: 0.9982 - val_loss: 0.3202 - v
```

```
# plot diagnostic learning curves
def summarize_diagnostics(histories):
  for i in range(len(histories)):
    # plot loss
```

```
        pyplot.subplot(2, 1, 1)
        pyplot.title('Cross Entropy Loss')
        pyplot.plot(histories[i].history['loss'], color='blue', label='train')
        pyplot.plot(histories[i].history['val_loss'], color='orange', label='test')
        pyplot.legend()
        # plot accuracy
        print('           ')
        pyplot.subplot(2, 1, 2)
        pyplot.title('Classification Accuracy')
        pyplot.plot(histories[i].history['accuracy'], color='blue', label='train')
        pyplot.plot(histories[i].history['val_accuracy'], color='orange', label='test')
    pyplot.legend()

    pyplot.show()

```

```
summarize_diagnostics(history)
```



Observation

Form the above graph and above output of training we can see that at epoch 6 the validation accuracy is 91% which is highest of all , after epoch 6 the accuracy on the training set increases but the validation accuracy starts to decrease which is sign of **Overfitting**.

At epoch 1 or 2 we can see that both of the training accuracy and validation accuracy is two low which shows underfitting.

Even from the graph, we can easily seee the underfitting of the model.

```
test_loss,test_acc = bclfr.evaluate(x_test,y_test,verbose=2)
```

```
24/24 - 0s - loss: 0.3646 - accuracy: 0.9107
```

```
probability_model = tf.keras.Sequential([bclfr])
predictions = probability_model.predict(x_test)
```

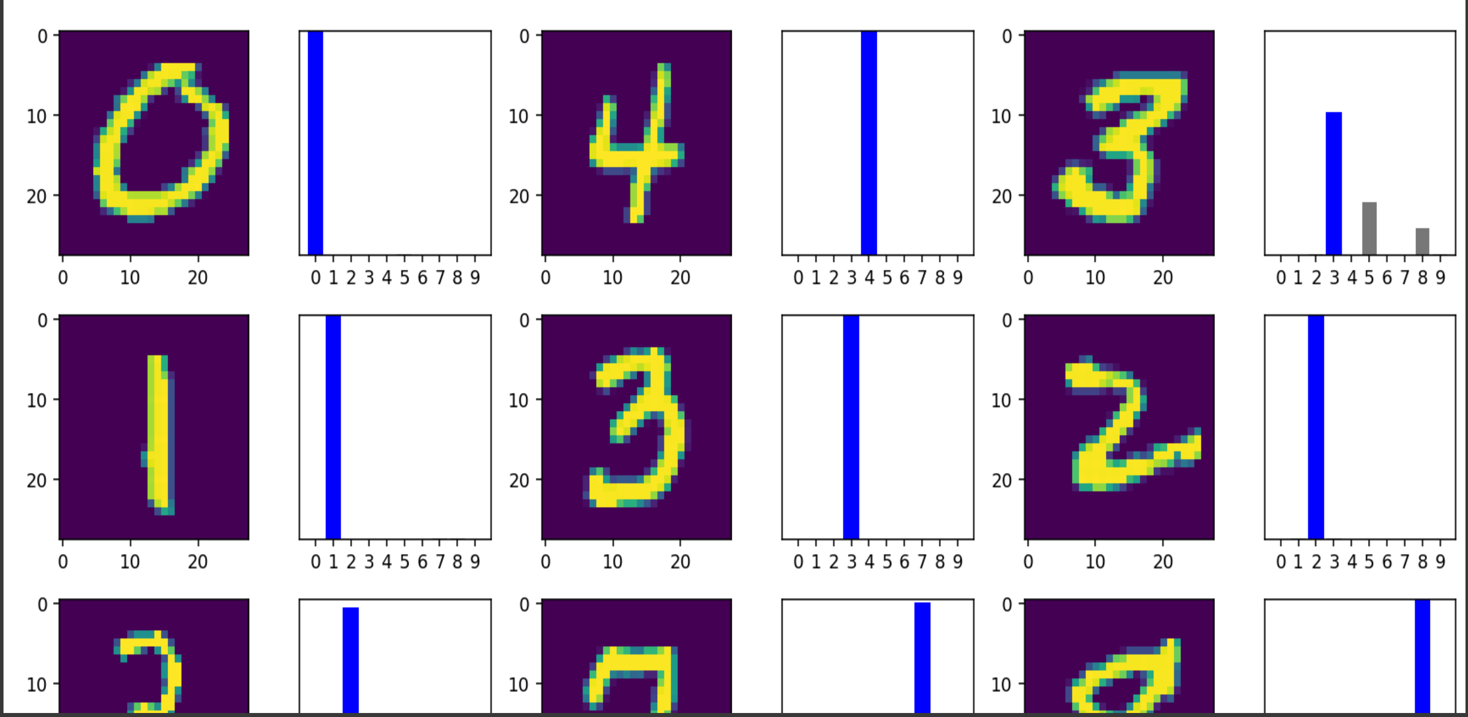
This function will plot a graph based on the results from the model trained above. It takes

- i - position
- prediction_array - The array of prediction predicted by my model.
- true_label - Actual label of test data set.

If the model predicted wrong result then the graph will be red, is the predicted result is right then the graph will be blue, if the model predicted some othe value but not confident about it the the graph is in the grey color.

```

def plot_value_array(i, predictions_array, true_label):
  predictions_array, true_label = predictions_array, true_label[i]
  plt.grid(False)

  plt.xticks(range(10))
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions_array)

  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

```
# Plot the first X test images, their predicted labels, and the true labels.
# Color correct predictions in blue and incorrect predictions in red.
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
  plt.subplot(num_rows, 2*num_cols, 2*i+1)
  plt.imshow(x_test[i].reshape(28,28))
  #plot_image(i, predictions[i], test_labels, test_images)
  plt.subplot(num_rows, 2*num_cols, 2*i+2)
  plot_value_array(i, predictions[i], y_test)
plt.tight_layout()
plt.show()
```



Observation

As we can see that the 3 is missclassified as 7 this may be because due to less training data . moreover that 3 looks much like 7.

All other test points are classified correctly

Comparison with PCA features

With only single layer

```
#PCA

data = pd.read_csv('17078PCA.csv')
pca_x =data.iloc[:,0:25].values
pca_y= data.iloc[:,25].values
print(len(pca_y))

#Spliting the data in training and test data
from sklearn.model_selection import train_test_split
pca_x_train,pca_x_test,pca_y_train,pca_y_test = train_test_split(pca_x,pca_y, test_size = 0.25, random_sta
```

```
3000
```

For this model, I have kept 25% of train data for testing and I has only single layer with input dimenssion as 25 and output is 10. I have used softmax as activation function.

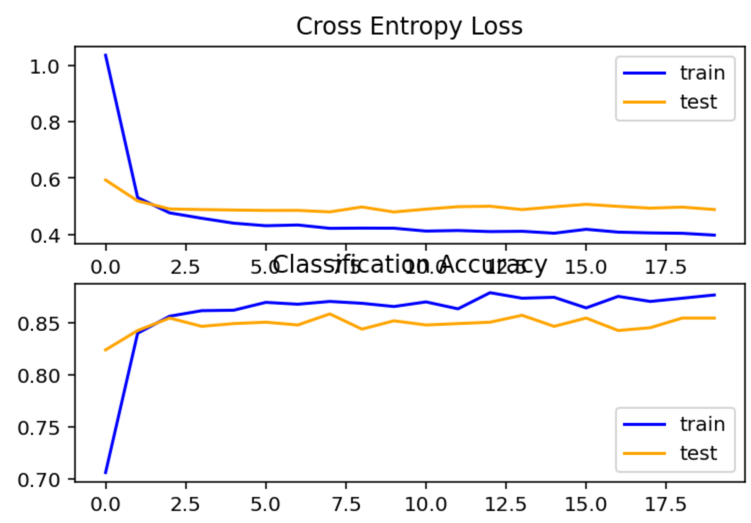
```
import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from torch import nn
pca = Sequential()
```

```
pca.add(Dense(units = 10 ,kernel_initializer ='uniform',activation = 'softmax', input_dim =25))

```

I am using stochastic gradient descent for optimizing with leaning rate of 0.01 and sparse_categorical_crossentrop as a loss function

```
pca.compile(optimizer=tf.keras.optimizers.Adam(0.01),loss='sparse_categorical_crossentropy',metrics=['accura
history1 =[]
history1.append(pca.fit(pca_x_train,pca_y_train,batch_size=64,epochs = 20,validation_data=(pca_x_test,pca_y

Epoch 1/20
36/36 [==============================] - 0s 5ms/step - loss: 1.0350 - accuracy: 0.7058 - val_loss: 0.5933 - v
Epoch 2/20
36/36 [==============================] - 0s 3ms/step - loss: 0.5313 - accuracy: 0.8400 - val_loss: 0.5193 - v
Epoch 3/20
36/36 [==============================] - 0s 3ms/step - loss: 0.4770 - accuracy: 0.8564 - val_loss: 0.4910 - v
Epoch 4/20
```

```python
summarize_diagnostics(history1)
```



```
36/36 [==============================] - 0s 3ms/step - loss: 0.4119 - accuracy: 0.8738 - val_loss: 0.4886 - v
```

Observation

With only one layer the accuracy, and 100 epoch, the training accuracy converges to ~ 88% even the validation accuracy is around 83% which is much less than the SVM model that I have done in previous assignmnet. It had a test accuracy of 96% . Now lets try adding more layers Here I have made a fully connected network. The input and hidden layer has **sigmoid** activation function, whereas the output layer has **softmax** activation function.

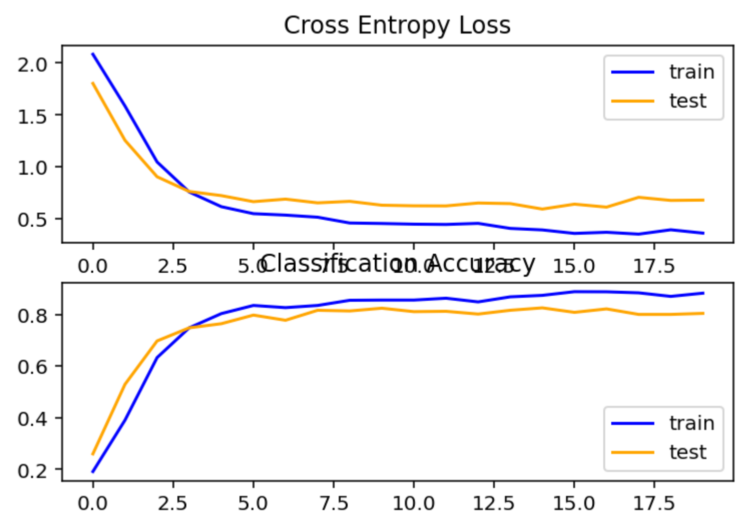
```
36/36 [==============================] - 0s 3ms/step - loss: 0.3982 - accuracy: 0.8769 - val_loss: 0.4889 - v
```

```python
import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from torch import nn
pca_with_hidden_layer = Sequential()

pca_with_hidden_layer.add(Dense(units = 20 ,kernel_initializer ='uniform',activation = 'sigmoid', input_dim =25
pca_with_hidden_layer.add(Dense(units=15,kernel_initializer='uniform',activation='sigmoid'))
pca_with_hidden_layer.add(Dense(units=10,kernel_initializer='uniform',activation='softmax'))


```

I am using stochastic gradient descent for optimizing with leaning rate of 0.01 and sparse_categorical_crossentrop as a loss function

```python
pca_with_hidden_layer.compile(optimizer=tf.keras.optimizers.Adam(0.1),loss='sparse_categorical_crossentrop
history2=[]
a=history2.append(pca_with_hidden_layer.fit(pca_x_train,pca_y_train,batch_size=64,epochs = 20,validation_d

Epoch 1/20
36/36 [==============================] - 0s 5ms/step - loss: 2.0839 - accuracy: 0.1916 - val_loss: 1.8033 - va
Epoch 2/20
36/36 [==============================] - 0s 4ms/step - loss: 1.5856 - accuracy: 0.3907 - val_loss: 1.2557 - va
Epoch 3/20
36/36 [==============================] - 0s 4ms/step - loss: 1.0475 - accuracy: 0.6329 - val_loss: 0.9052 - va
Epoch 4/20
36/36 [==============================] - 0s 4ms/step - loss: 0.7587 - accuracy: 0.7480 - val_loss: 0.7637 - v
Epoch 5/20
36/36 [==============================] - 0s 3ms/step - loss: 0.6174 - accuracy: 0.8031 - val_loss: 0.7239 - va
Epoch 6/20
36/36 [==============================] - 0s 3ms/step - loss: 0.5501 - accuracy: 0.8347 - val_loss: 0.6656 - va
Epoch 7/20
36/36 [==============================] - 0s 3ms/step - loss: 0.5362 - accuracy: 0.8262 - val_loss: 0.6900 - v
Epoch 8/20
36/36 [==============================] - 0s 3ms/step - loss: 0.5160 - accuracy: 0.8347 - val_loss: 0.6541 - va
Epoch 9/20
36/36 [==============================] - 0s 3ms/step - loss: 0.4604 - accuracy: 0.8547 - val_loss: 0.6686 - v
Epoch 10/20
36/36 [==============================] - 0s 4ms/step - loss: 0.4556 - accuracy: 0.8556 - val_loss: 0.6315 - va
Epoch 11/20
36/36 [==============================] - 0s 4ms/step - loss: 0.4491 - accuracy: 0.8556 - val_loss: 0.6257 - va
Epoch 12/20
36/36 [==============================] - 0s 3ms/step - loss: 0.4463 - accuracy: 0.8627 - val_loss: 0.6247 - v
Epoch 13/20
36/36 [==============================] - 0s 3ms/step - loss: 0.4567 - accuracy: 0.8484 - val_loss: 0.6527 - v
Epoch 14/20
36/36 [==============================] - 0s 3ms/step - loss: 0.4083 - accuracy: 0.8680 - val_loss: 0.6469 - v
Epoch 15/20
36/36 [==============================] - 0s 3ms/step - loss: 0.3937 - accuracy: 0.8738 - val_loss: 0.5943 - v
Epoch 16/20
36/36 [==============================] - 0s 3ms/step - loss: 0.3601 - accuracy: 0.8880 - val_loss: 0.6415 - va
Epoch 17/20
36/36 [==============================] - 0s 3ms/step - loss: 0.3711 - accuracy: 0.8876 - val_loss: 0.6130 - va
Epoch 18/20
36/36 [==============================] - 0s 3ms/step - loss: 0.3533 - accuracy: 0.8836 - val_loss: 0.7074 - v
Epoch 19/20
36/36 [==============================] - 0s 4ms/step - loss: 0.3950 - accuracy: 0.8698 - val_loss: 0.6776 - v
Epoch 20/20
36/36 [==============================] - 0s 3ms/step - loss: 0.3630 - accuracy: 0.8822 - val_loss: 0.6807 - v
```

```
summarize_diagnostics(history2)
```



Observation

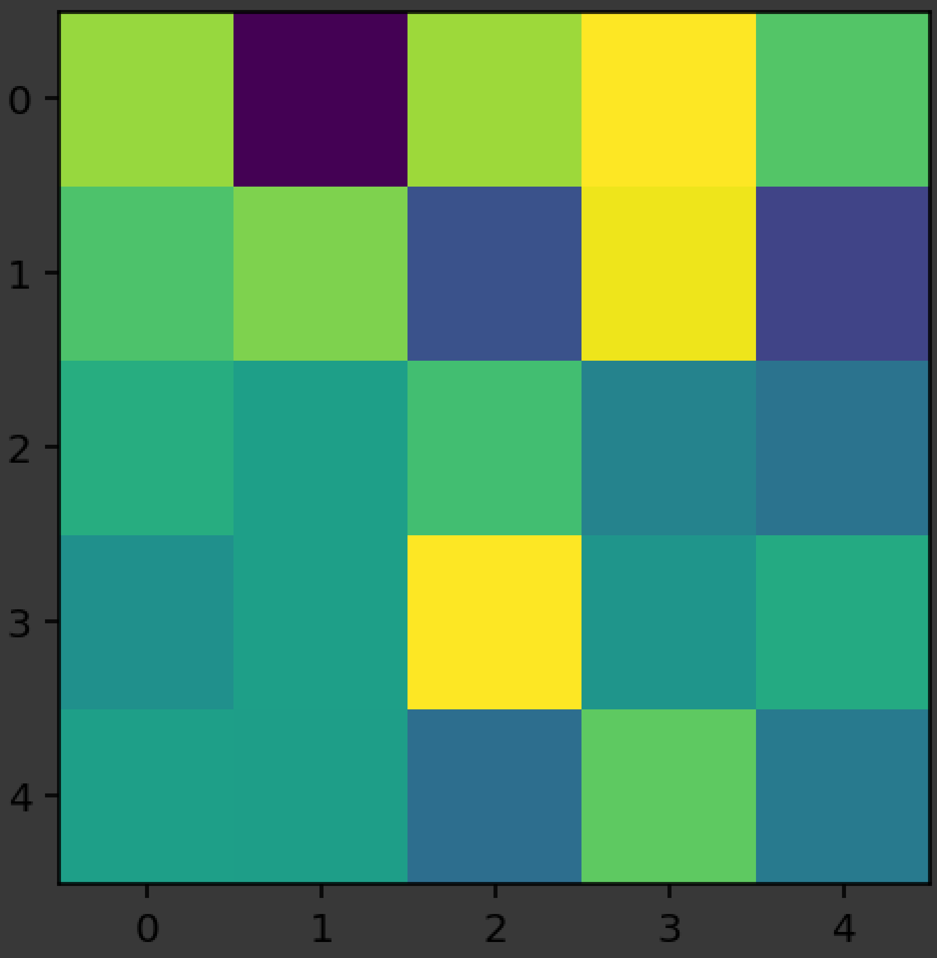
After 20 epoch accuracy has increased as I have increased the depth of of the nural network. It is because by adding the hidden layer I gave the network flexibility to fit to the data but also incresed the complexity of the basis function.

```
test_loss,test_acc = pca_with_hidden_layer.evaluate(pca_x_test,pca_y_test,verbose=2)
probability_model = tf.keras.Sequential([pca_with_hidden_layer])
predictions = probability_model.predict(pca_x_test)
```

```
24/24 - 0s - loss: 0.6953 - accuracy: 0.8240
```

Visulalization of the above model

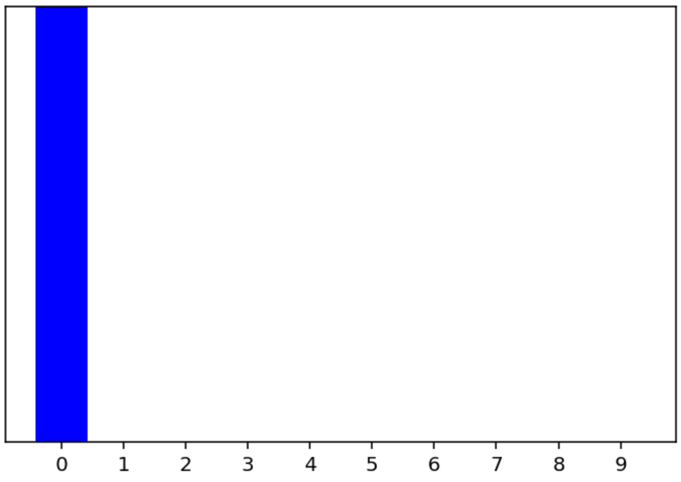
Ploting the graph with true label, I havent shown the image based on the features given in the data set because they don't make sense to human. It is something like this Therefore I have printed the true lable against the predicted value.



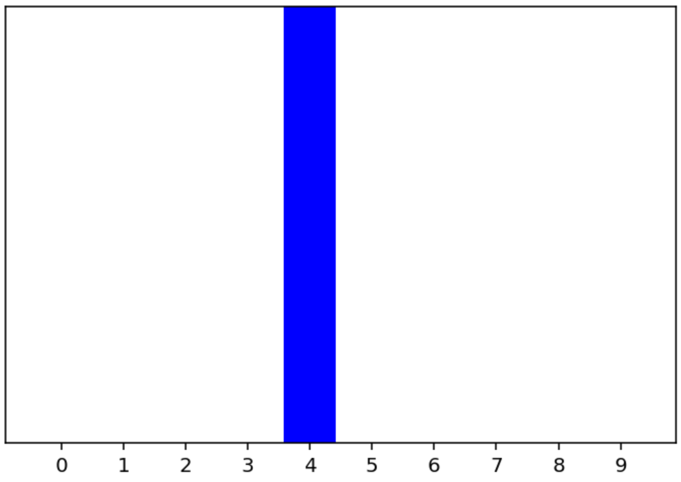
```
# Plot the first X test images, their predicted labels, and the true labels.
# Color correct predictions in blue and incorrect predictions in red.


for i in range(0,10):

  plot_value_array(i, predictions[i], pca_y_test)
  print('-----------------------------------------------------------------------------------------------')
  print('Test(Actual) value =',pca_y_test[i])


```

```
plt.show()
```

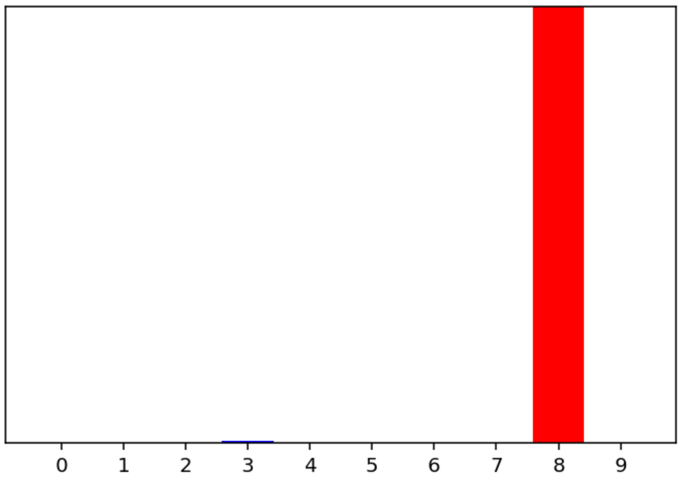
Test(Actual) value = 0



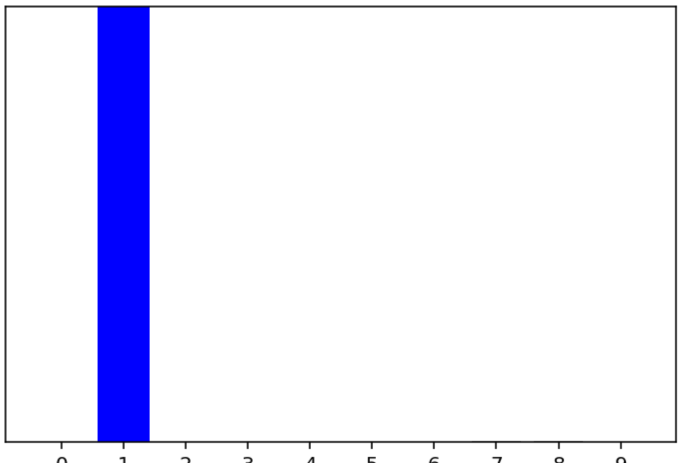
Test(Actual) value = 4



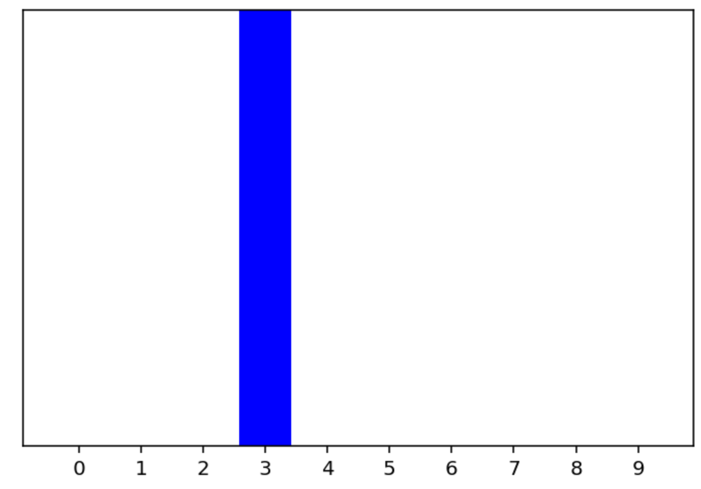
Test(Actual) value = 3



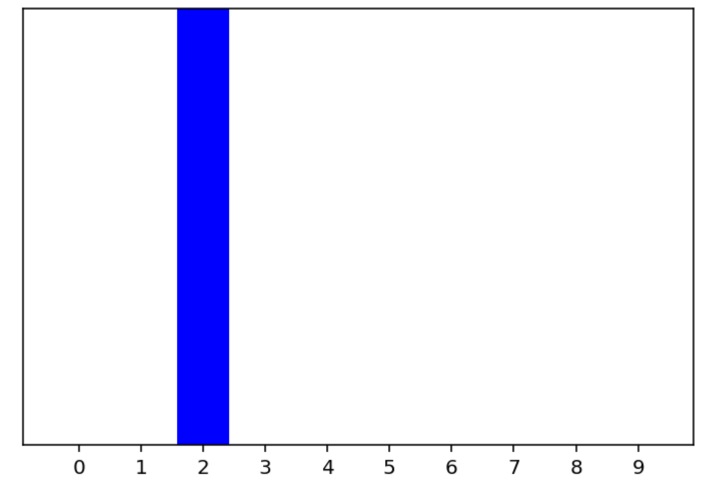
Test(Actual) value = 1



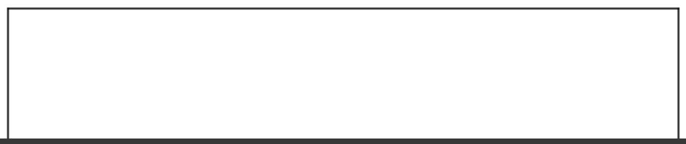
```
-----------------------------------------------------------------------------------------
Test(Actual) value = 3
```



```
-----------------------------------------------------------------------------------------
Test(Actual) value = 2
```



```
-----------------------------------------------------------------------------------------
Test(Actual) value = 2
```



CNN for MNIST Handwritten Digit Classification

As suggested, I am downloading the full mnist data from here. I downloaded all data set then i decompresses them and then using idx2numpy library i converted them to the numpy array.

```
!wget http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
!wget http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
!wget http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
!wget http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
```

```
--2020-06-28 14:05:05--  http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Resolving yann.lecun.com (yann.lecun.com)... 104.28.6.204, 104.28.7.204, 172.67.171.76, ...
Connecting to yann.lecun.com (yann.lecun.com)|104.28.6.204|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 28881 (28K) [application/x-gzip]
Saving to: 'train-labels-idx1-ubyte.gz.1'

train-labels-idx1-u 100%[===================>]  28.20K  --.-KB/s    in 0.01s

2020-06-28 14:05:05 (2.04 MB/s) - 'train-labels-idx1-ubyte.gz.1' saved [28881/28881]

--2020-06-28 14:05:12--  http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Resolving yann.lecun.com (yann.lecun.com)... 172.67.171.76, 104.28.6.204, 104.28.7.204, ...
Connecting to yann.lecun.com (yann.lecun.com)|172.67.171.76|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 9912422 (9.5M) [application/x-gzip]
Saving to: 'train-images-idx3-ubyte.gz.1'

train-images-idx3-u 100%[===================>]   9.45M  60.6MB/s    in 0.2s

2020-06-28 14:05:12 (60.6 MB/s) - 'train-images-idx3-ubyte.gz.1' saved [9912422/9912422]

--2020-06-28 14:05:19--  http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Resolving yann.lecun.com (yann.lecun.com)... 104.28.6.204, 104.28.7.204, 172.67.171.76, ...
Connecting to yann.lecun.com (yann.lecun.com)|104.28.6.204|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1648877 (1.6M) [application/x-gzip]
Saving to: 't10k-images-idx3-ubyte.gz.1'

t10k-images-idx3-ub 100%[===================>]   1.57M  --.-KB/s    in 0.1s

2020-06-28 14:05:19 (14.1 MB/s) - 't10k-images-idx3-ubyte.gz.1' saved [1648877/1648877]

--2020-06-28 14:05:24--  http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Resolving yann.lecun.com (yann.lecun.com)... 104.28.6.204, 104.28.7.204, 172.67.171.76, ...
Connecting to yann.lecun.com (yann.lecun.com)|104.28.6.204|:80... connected.
```

```
!pip install idx2numpy
```

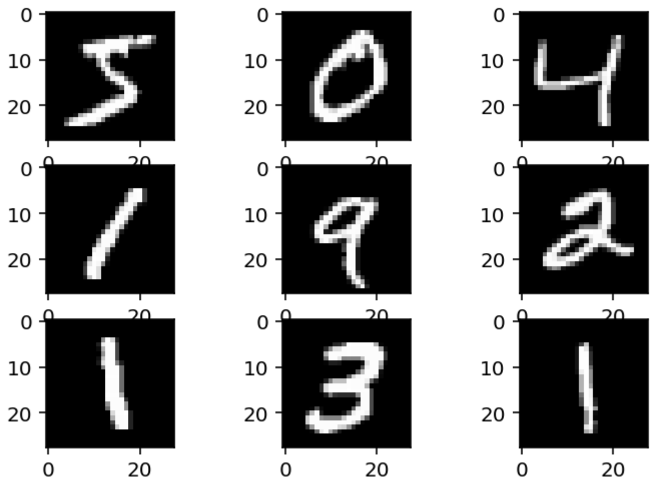
```
Collecting idx2numpy
  Downloading https://files.pythonhosted.org/packages/23/6b/abab4652eb249f432c62431907c8de32bdcedb
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from idx2numpy) (1.18.5)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from idx2numpy) (1.12.0)
Building wheels for collected packages: idx2numpy
  Building wheel for idx2numpy (setup.py) ... done
  Created wheel for idx2numpy: filename=idx2numpy-1.2.2-cp36-none-any.whl size=8032 sha256=1c88c3da2cfd
  Stored in directory: /root/.cache/pip/wheels/7a/b5/69/3e0757b3086607e95db70661798fdf98a77a0bb79
Successfully built idx2numpy
Installing collected packages: idx2numpy
Successfully installed idx2numpy-1.2.2
```

converting MNIST data to numpy array.

```python
import idx2numpy
import numpy as np
train_images = idx2numpy.convert_from_file('/content/drive/My Drive/Assignment4/train-images-idx3-ubyte
test_images = idx2numpy.convert_from_file('/content/drive/My Drive/Assignment4/t10k-images-idx3-ubyte/
train_label = idx2numpy.convert_from_file('/content/drive/My Drive/Assignment4/train-labels-idx1-ubyte/tr
test_label = idx2numpy.convert_from_file('/content/drive/My Drive/Assignment4/t10k-labels-idx1-ubyte/t10
```

```python
from keras.datasets import mnist
from matplotlib import pyplot
# load dataset

# summarize loaded dataset
print('Train: X=%s, y=%s' % (train_images.shape, train_label.shape))
print('Test: X=%s, y=%s' % (test_images.shape, test_label.shape))
# plot first few images
for i in range(9):
  # define subplot
  pyplot.subplot(330 + 1 + i)
  # plot raw pixel data
  pyplot.imshow(train_images[i], cmap=pyplot.get_cmap('gray'))
# show the figure
pyplot.show()
```

```
Train: X=(60000, 28, 28), y=(60000,)
Test: X=(10000, 28, 28), y=(10000,)
```



we know that the images are all pre-aligned (e.g. each image only contains a hand-drawn digit), that the images all have the same square size of 28×28 pixels, and that the images are grayscale. load the images and reshape the data arrays to have a single color channel.

```
trainX = train_images.reshape((train_images.shape[0], 28, 28, 1))
testX = test_images.reshape((test_images.shape[0], 28, 28, 1))
```

Using a one hot encoding for the class element of each sample, transforming the integer into a 10 element binary vector with a 1 for the index of the class value, and 0 values for all other classes.

```
from keras.utils import to_categorical
trainY = to_categorical(train_label)
testY = to_categorical(test_label)
```

```
def load_dataset():

  # reshape dataset to have a single channel
  trainX = train_images.reshape((train_images.shape[0], 28, 28, 1))
  testX = test_images.reshape((test_images.shape[0], 28, 28, 1))
  # one hot encode target values
  trainY = to_categorical(train_label)
  testY = to_categorical(test_label)
  return trainX, trainY, testX, testY
```

Rescaling image value from [0,255] to [0,1]

```
# scale pixels
def prep_pixels(train, test):
  # convert from integers to floats
  train_norm = train.astype('float32')
  test_norm = test.astype('float32')
  # normalize to range 0-1
  train_norm = train_norm / 255.0
  test_norm = test_norm / 255.0
  # return normalized images
  return train_norm, test_norm
```

Defining Model

For convolution front-end , I will start with single Convolution layer with small filter size (3,3) and a modest number of filter (32) followed by a max polling layer. The filter maps can then be flattened to provide features to the classifier . I will be using Softmax activation function. in between the feature extrator and output layer I will adda dense layer to interpret the features, 100 nodes

All layer will use reLU activation function and He weight initialization scheme.

I will use stochastic gradient decent optimizer with learning rate of 0.01 and momentum 0.9. The categorical cross-entropy loss function will be optimized, suitable for multi-class classification, and I will monitor the classification accuracy metric, which is appropriate given we have the same number of examples in each of the 10 classes.

```
# define cnn model
def define_model():
  model = Sequential()
  model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', input_shape=(28, 28, 1)))
  model.add(MaxPooling2D((2, 2)))
  model.add(Flatten())
  model.add(Dense(100, activation='relu', kernel_initializer='he_uniform'))
  model.add(Dense(10, activation='softmax'))
  # compile model
  opt = SGD(lr=0.01, momentum=0.9)
  model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
  return model
```

The evaluate_model() function below implements these behaviors, taking the training dataset as arguments and returning a list of accuracy scores

```

from numpy import mean
from numpy import std
from sklearn.model_selection import KFold
from sklearn.model_selection import KFold
from keras.datasets import mnist
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Dense
from keras.layers import Flatten
from keras.optimizers import SGD
def evaluate_model(dataX, dataY, n_folds=5):
  scores, histories = list(), list()
  # prepare cross validation
  kfold = KFold(n_folds, shuffle=True, random_state=1)
  # enumerate splits
  for train_ix, test_ix in kfold.split(dataX):
    # define model
    model = define_model()
    # select rows for train and test
    trainX, trainY, testX, testY = dataX[train_ix], dataY[train_ix], dataX[test_ix], dataY[test_ix]
    # fit model
    history = model.fit(trainX, trainY, epochs=10, batch_size=32, validation_data=(testX, testY), verbose=0)
    # evaluate model
    _, acc = model.evaluate(testX, testY, verbose=0)
    print('> %.3f' % (acc * 100.0))
    # stores scores
    scores.append(acc)
    histories.append(history)
  return scores, histories
```

```
# summarize model performance
def summarize_performance(scores):
  # print summary
  print('Accuracy: mean=%.3f std=%.3f, n=%d' % (mean(scores)*100, std(scores)*100, len(scores)))
  # box and whisker plots of results
  pyplot.boxplot(scores)
  pyplot.show()
```

```
# summarize model performance
def summarize_performance(scores):
  # print summary
  print('Accuracy: mean=%.3f std=%.3f, n=%d' % (mean(scores)*100, std(scores)*100, len(scores)))
  # box and whisker plots of results
  pyplot.boxplot(scores)
  pyplot.show()

```

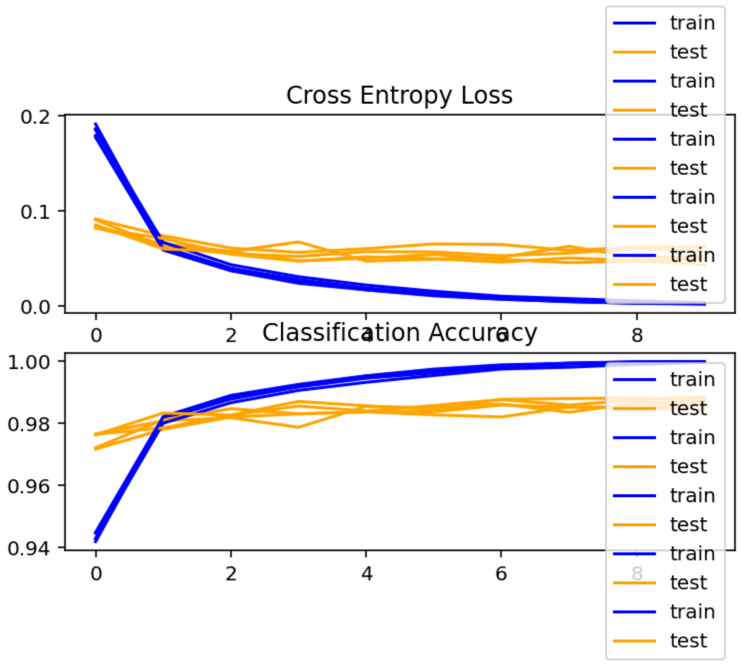
```

def run_test_harness():
  # load dataset
  trainX, trainY, testX, testY = load_dataset()
  # prepare pixel data
  trainX, testX = prep_pixels(trainX, testX)
  # evaluate model
  scores, histories = evaluate_model(trainX, trainY)
  # learning curves
  summarize_diagnostics(histories)
  # summarize estimated performance
  summarize_performance(scores)
```

```
run_test_harness()
```

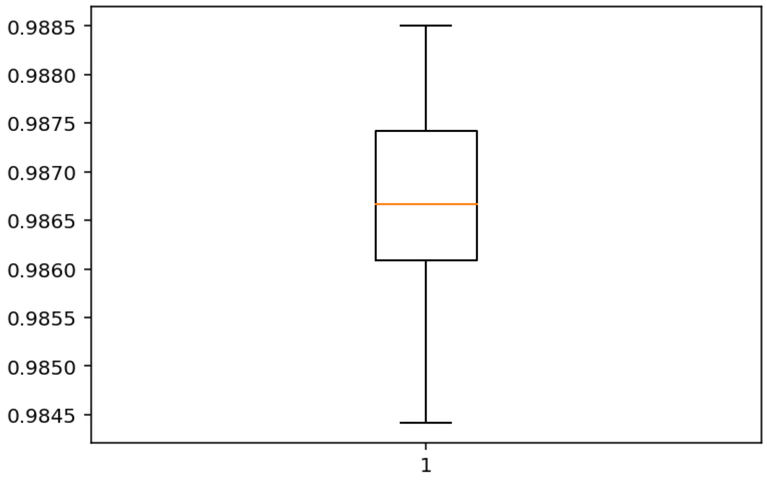
```
1   run_test_harness()
```

```
> 98.442
> 98.667
> 98.608
> 98.850
> 98.742
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: MatplotlibDeprecationWarning: Adding an axe
  """
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:12: MatplotlibDeprecationWarning: Adding an ax
  if sys.path[0] == '':
```



```
Accuracy: mean=98.662 std=0.136, n=5
```



The model achieves a good fit, with train and test learning curves converging. There is no obvious sign of over- or underfitting. A box and whisker plot is created to summarize the distribution of accuracy scores.

Yes these are more natural or intuitive than the representations learnt by the standard neural net.

Batch normalization can be used after convolutional and fully connected layers. It has the effect of changing the distribution of the output of the layer, specifically by standardizing the outputs. This has the effect of stabilizing and accelerating the learning process.

As we increse the depth of the network the accuracy increases to 99%